

Research Article

Pupil Heart Rate Variability Monitoring Via Pupillary Fluctuations on Mobile DevicesGunda Sahitya¹, Sangu Girija², Gorantla Madhuri³, Mudavath Praveen Kumar⁴ and G.Swathi Reddy^{5,*}¹⁻⁴Student, Department of CSE(AI&ML), Samskruti College of Engineering & Technology, Hyderabad, Telangana, 500001, India.⁵Assistant Professor, Department of CSE(AI&ML), Samskruti College of Engineering & Technology, Hyderabad, Telangana, 500001, India.

*Corresponding Author: G.Swathi Reddy. Email: gswathi.reddy454@gmail.com

Received: 12/10/2025; Revised: 29/11/2025; Accepted: 25/12/2025; Published: 31/12/2025.

DOI: <https://doi.org/10.69996/fmep.2025027>

Abstract: Heart Rate Variability (HRV) is a critical physiological marker used to assess autonomic nervous system activity and overall cardiovascular health. Traditional HRV monitoring relies on electrocardiograms (ECG) or wearable sensors, which can be intrusive, costly, and inconvenient for continuous use. This paper presents *PUPILHEART*, an innovative mobile-based system that leverages pupillary fluctuations—captured through smartphone cameras—as a non-contact alternative for HRV analysis. The proposed framework integrates a one-dimensional convolutional neural network (1D-CNN) with a recurrent neural network (RNN) to extract spatial and temporal features from real-time video data, enabling accurate HRV classification and prediction. The system is designed with intuitive user interfaces for external users and health analysts, ensuring ease of access and deployment. Extensive experimental analysis demonstrates high performance in terms of accuracy, sensitivity, and latency, validating the system's effectiveness in real-world scenarios. *PUPILHEART* offers a scalable, privacy-conscious, and hardware-efficient solution for continuous cardiac monitoring, setting a new direction in mobile health diagnostics and preventive care.

Keywords: Heart Rate Variability (HRV), Pupillary Fluctuations, Mobile Health (mHealth), One-Dimensional Convolutional Neural Network (1D-CNN), Recurrent Neural Network (RNN).

1.Introduction

Heart Rate Variability (HRV) is a non-invasive measure of autonomic nervous system (ANS) function and a key biomarker in the assessment of cardiovascular health, stress levels, mental workload, and sleep quality [1]. Traditional methods for HRV monitoring, such as electrocardiography (ECG) or photoplethysmography (PPG), although clinically robust, are often constrained by the need for wearable sensors, electrode placement, and dedicated hardware. These limitations restrict continuous and ubiquitous HRV tracking in daily life. With the growing demand for accessible health monitoring tools, there is a critical need to explore alternative physiological signals that can be harnessed through widely available devices like smartphones [2]. Pupillometry — the measurement of pupil diameter and dynamics — has emerged as a promising proxy for ANS activity. The pupil is innervated by both sympathetic and parasympathetic branches of the ANS, leading to diameter fluctuations that reflect underlying physiological and emotional states [3]. Changes in pupil size have been shown to correlate with cognitive load, emotional arousal, and stress — all of which influence HRV [4]. Recent research has uncovered statistically significant relationships between spontaneous pupillary fluctuations and cardiovascular metrics, including heart rate and its variability [5]. This relationship lays the foundation for an indirect, contactless method of HRV assessment via pupillometry.



The evolution of mobile technology and front-facing camera capabilities has opened new avenues for real-time, camera-based physiological measurements [6]. Leveraging mobile device cameras to extract subtle biological signals — such as blood flow, respiratory rate, and eye movements — is a growing field known as "mobile health sensing" or "smartphone biosensing" [7]. The feasibility of pupil detection through mobile video capture, coupled with advances in machine learning and computer vision, allows the extraction of high-resolution temporal pupil data [8]. This enables a paradigm shift from conventional wearable HRV monitoring to an easily deployable, sensorless, vision-based method.

Several studies have explored the potential of pupillary dynamics for inferring cognitive and physiological states. For instance, Beatty and Lucero-Wagoner demonstrated that task-evoked pupillary responses reflect cognitive workload, while Granholm and Verney linked pupil size fluctuations with information processing load in schizophrenia research. Similarly, adaptive thresholding techniques, edge-detection filters, and deep learning architectures such as YOLO, U-Net, and MobileNet have shown efficacy in tracking ocular features from mobile-captured videos. Despite these advancements, the direct translation of pupillary features into HRV metrics remains underexplored, especially in real-world, non-clinical environments. Moreover, the integration of pupil-based physiological measurements into mobile applications aligns with the broader trend of personalized, ambient health intelligence. In the context of digital health, such a system offers a unique opportunity to assess emotional and cardiovascular health passively and continuously without the need for wearable devices or physical contact. This is particularly advantageous for remote monitoring of vulnerable populations, such as older adults or individuals with cardiovascular risk, as well as for mental health applications like anxiety and stress detection.

Mobile-based pupillometry presents both opportunities and challenges. On the one hand, mobile devices are ubiquitous, cost-effective, and user-friendly. On the other hand, they pose constraints such as camera quality, illumination conditions, and motion artifacts. Therefore, a reliable, lightweight framework is needed to overcome these barriers and transform pupillary video data into clinically meaningful HRV metrics. This necessitates an interdisciplinary approach combining signal processing, computer vision, biomedical engineering, and mobile application development. In this context, the proposed research introduces PUPILHEART, a novel framework for HRV estimation based on pupillary fluctuation analysis using mobile devices. By tracking subtle, involuntary changes in pupil size captured through smartphone cameras and correlating them with HRV markers, the system aims to establish a contactless, convenient, and scalable solution for real-time cardiovascular monitoring. Unlike prior works that rely on external sensors or laboratory-grade cameras, this study emphasizes the use of off-the-shelf mobile hardware, ensuring real-world applicability and accessibility.

2. Related Works

Recent advancements in non-invasive health monitoring have catalyzed research in alternative modalities for physiological signal extraction beyond conventional ECG or PPG-based methods. A growing body of literature has explored the potential of camera-based biosensing, especially using front-facing mobile cameras, to derive key metrics such as heart rate, respiratory rate, and blood oxygen saturation without physical contact. These approaches leverage ambient light, skin reflectance, and pixel intensity fluctuations to measure physiological changes, but often suffer from motion artifacts, low-light sensitivity, and skin tone variability. To overcome these challenges, researchers have turned to ocular features, particularly pupil dynamics, as a robust marker of autonomic nervous system activity. Pupillary fluctuation, controlled by both sympathetic and parasympathetic systems, reflects stress, cognitive load, and arousal—factors intricately linked with HRV.

In recent years, there has been a rapid surge in the development and application of mobile health (mHealth) technologies, with a growing emphasis on visual, interactive, and user-centric platforms. Chan et al. [9] systematically reviewed health visualizations on mobile devices and emphasized the critical role of intuitive, dynamic data representation in enhancing user engagement and comprehension. This insight directly aligns with the PUPILHEART framework's goal of translating complex HRV metrics derived from pupillary fluctuations into easily interpretable visual feedback for users. Complementing this, Girela-Serrano et al. [10] explored the psychological implications of mobile device usage among children and adolescents, highlighting the dual-edged nature of mHealth tools. While they can facilitate monitoring and intervention, excessive or poorly designed interfaces could exacerbate mental health issues—underscoring the need for ethical and minimally invasive systems like PUPILHEART. The integration of federated learning in mHealth, as examined by Wang et al. [11], presents a privacy-conscious approach to handling sensitive biometric data, making it particularly suitable for frameworks dealing with personalized signals like pupillometry. Similarly, Fahed et al. [12] compared voice features from studio and mobile device recordings, underscoring that even consumer-grade devices can effectively capture biometric features—a precedent supporting the feasibility of mobile-based pupillary data collection. From a healthcare policy perspective, Demir et al. [13] demonstrated the impact of simulation-driven evaluations of mobile interventions in Nigeria, suggesting that data-driven modeling can inform public health decisions, much like how PUPILHEART could inform early interventions for stress or cardiovascular risk.

On the educational and user-perception front, Hamad et al. [14] investigated the attitudes of health science students toward mobile learning, revealing a generally positive reception that bodes well for mHealth adoption. In parallel, Xodabande and Hashemi [15] reported improved vocabulary development among university students using mobile e-textbooks, reinforcing the cognitive benefits of interactive mobile platforms. Vassallo [16] and Chib & Li [17] both stressed the necessity for evidence-based and context-aware mHealth applications in both developed and developing countries, advocating for interventions grounded in rigorous clinical and technical validation, as proposed in the PUPILHEART system. Security and privacy, fundamental pillars of digital health, were addressed by Aminifar et al. [18], who developed a privacy-preserving federated learning model tailored for intelligent mHealth systems. This is especially pertinent for systems like PUPILHEART that collect sensitive ocular and HRV data. Okolo et al. [19] critically reviewed how mHealth applications improve patient engagement and health outcomes, highlighting factors such as personalization, real-time feedback, and accessibility—all of which are core design tenets of the PUPILHEART system.

On the technological infrastructure side, Singhal et al. [20] presented a hybrid blockchain-deep learning architecture for analyzing electronic health records, showing how emerging technologies can be used to secure and process medical data efficiently. Ethical considerations were rigorously analyzed by Amugongo et al. [21], who proposed embedding AI ethics throughout the agile development cycle of mHealth applications—a methodology relevant to PUPILHEART's development given its AI-driven inference on personal biometrics. Mindu et al. [22] discussed the implementation challenges of digital mental health tools in rural South Africa, emphasizing the importance of affordability, simplicity, and cultural fit—critical for deploying PUPILHEART in diverse environments.

From a behavioral modeling standpoint, Walle et al. [23] used the UTAUT-2 model to predict diabetes patients' intention to use wearable devices, identifying factors such as

performance expectancy and ease of use, which can similarly influence user adoption of vision-based HRV monitoring apps. Liu and Hwang [24] highlighted the evolving role of touchscreen devices in early education, illustrating their influence in shaping user behavior, interface design, and attention—considerations that must be factored into user experience (UX) for health-oriented mobile apps. Finally, Chen et al. [25] presented the concept of a human digital twin enabled by mobile AI-generated content (AIGC), showcasing how personalized health monitoring through smartphones is converging toward real-time, predictive, and autonomous systems—a trajectory aligned with the vision of PUPILHEART.

The increasing adoption of mobile health (mHealth) technologies and the promising insights from pupillometry into autonomic nervous system (ANS) activity, there remains a significant void in integrating pupillary dynamics with heart rate variability (HRV) monitoring on mobile platforms. Existing methods for HRV measurement still rely heavily on contact-based sensors such as ECG or PPG, which, although clinically accurate, are inconvenient for continuous and passive monitoring in real-world settings. While recent studies have explored the use of smartphone cameras for non-contact biosensing, these are predominantly limited to facial photoplethysmographic (rPPG) techniques and lack robustness in motion-prone or low-light environments. Furthermore, although prior research has established the physiological correlation between pupil fluctuations and ANS activity, there is a lack of practical frameworks that leverage this relationship to extract quantitative HRV metrics from mobile-acquired ocular data. No existing solution offers a real-time, contactless, mobile-based HRV monitoring system grounded in pupillary behavior, particularly one that is lightweight, user-adaptive, and deployable in unconstrained environments. Additionally, current mobile health solutions rarely integrate ethical AI design, privacy-aware computation, and explainable inference in a single, cohesive pipeline. Thus, a critical gap exists at the intersection of pupillometry, mobile computing, AI-based physiological modeling, and user-centric health feedback, which this research aims to address through the proposed PUPILHEART system.

3. Proposed one-dimensional convolutional neural network

To estimate heart rate variability (HRV) from time-series pupil diameter data acquired via mobile device cameras, this study proposes a lightweight yet effective One-Dimensional Convolutional Neural Network (1D-CNN) model. The rationale for selecting a 1D-CNN stems from its proven effectiveness in handling sequential biomedical signals, such as ECG, EMG, and other physiological waveforms, while maintaining computational efficiency suitable for real-time mobile deployment. In the PUPILHEART framework, the raw video frames captured from the front-facing camera are processed through a pre-trained eye segmentation model to extract pupil diameter over time. This continuous signal, representing involuntary pupillary fluctuations, is normalized and segmented into fixed-length windows, each treated as a 1D input vector for the CNN. The proposed 1D-CNN architecture consists of multiple convolutional layers with progressively increasing filter sizes to capture both fine-grained and high-level temporal patterns in pupil oscillation. Each convolutional layer is followed by a ReLU activation function and a max-pooling layer to reduce dimensionality and mitigate overfitting. Batch normalization is applied to improve convergence speed and stabilize training. The final feature maps are flattened and passed through one or more fully connected layers, culminating in a regression output layer that estimates core HRV metrics such as RMSSD (Root Mean Square of Successive Differences), SDNN (Standard Deviation of NN intervals), and LF/HF ratio (Low-to-High Frequency power ratio). The network is trained using a mean squared error (MSE) loss function to minimize deviation from ground-truth HRV values computed from reference ECG signals.

To enhance model generalizability and reduce dependency on specific lighting or device conditions, data augmentation techniques such as Gaussian noise injection and time-series

jittering are applied during training. The model is optimized using the Adam optimizer with a learning rate scheduler, and early stopping is employed to prevent overfitting. Given its low parameter count and real-time inference capability, the 1D-CNN model is well-suited for deployment on edge devices such as smartphones and tablets without requiring GPU acceleration. Overall, the proposed 1D-CNN serves as the core analytical engine within PUPILHEART, enabling accurate and efficient HRV estimation from mobile-captured pupillary signals in an entirely contactless manner. The raw input to the system originates from the front-facing camera of a smartphone, capturing a video of the user's eye under normal lighting conditions. Using a deep-learning-based segmentation model, the eye region is extracted, and the pupil diameter is measured frame-by-frame through contour fitting and ellipse approximation. The resulting signal, typically noisy due to ambient light variation and micro-blinks, is preprocessed with normalization, low-pass filtering, and artifact suppression to retain only the relevant autonomic fluctuations. The cleaned pupil time series is then segmented into overlapping windows, each representing a short duration of activity (e.g., 30 seconds), which serves as the input vector to the 1D-CNN.

The proposed 1D-CNN architecture comprises four main convolutional blocks, each consisting of a 1D convolutional layer, ReLU activation, max pooling, and batch normalization. The early layers use small filter sizes (e.g., 3 or 5) to detect fine-scale changes in pupil diameter that correlate with high-frequency HRV components. Subsequent layers adopt larger filters (e.g., 7 or 9) to capture lower-frequency variations associated with parasympathetic and sympathetic nervous system activity. This hierarchical structure ensures that the network can learn a multiscale temporal representation of the input signal. After the convolutional layers, the output is flattened and passed through a dense fully connected layer with dropout regularization to prevent overfitting. The final output layer performs regression to predict key HRV metrics, such as RMSSD, SDNN, pNN50, and LF/HF ratio, all of which are commonly used indicators of cardiac autonomic modulation. The model is trained using the Mean Squared Error (MSE) loss function and optimized with the Adam optimizer. A cyclical learning rate and early stopping are employed to ensure fast convergence and generalization across different user conditions and devices.

To account for the variability in real-world conditions, data augmentation techniques are applied during training. These include amplitude scaling, time warping, Gaussian noise addition, and temporal shifting, which simulate different eye movement speeds and lighting artifacts. This not only improves the model's robustness but also allows it to generalize across diverse users and mobile environments. Compared to traditional HRV estimation methods that rely on contact-based sensors or ECG acquisition, the 1D-CNN within PUPILHEART provides a non-invasive, camera-only alternative with minimal setup. The model is optimized to run efficiently on mobile CPUs without dedicated GPU acceleration, ensuring real-time operation. In summary, the proposed 1D-CNN serves as the analytical core of PUPILHEART, enabling reliable, continuous, and contactless HRV estimation from spontaneous pupillary fluctuations captured via everyday smartphones.

4. Classification with integrated one-dimensional convolutional neural network with RNN

To enhance the predictive performance of the PUPILHEART system, this research integrates a One-Dimensional Convolutional Neural Network (1D-CNN) with a Recurrent Neural Network (RNN), forming a hybrid deep learning architecture for robust classification of

heart rate variability (HRV) states derived from pupillary fluctuations. While 1D-CNNs are highly efficient in extracting spatial-temporal patterns from time-series data, RNNs are particularly adept at modeling sequential dependencies and long-range temporal correlations—critical in accurately classifying physiological rhythms that evolve over time. The integrated model processes a sequence of normalized pupil diameter values, $x = \{x_1, x_2, \dots, x_T\}$, where each x_t corresponds to the pupil size at time step t . The 1D-CNN serves as the feature extractor, learning localized fluctuation patterns through a series of convolutional layers. The output feature map from the CNN, denoted as $F = \{f_1, f_2, \dots, f_k\}$, is then fed into the RNN block to capture temporal dependencies. The RNN computes the hidden state at each time step h_t stated in equation (1)

$$h_t = \tanh(W_h \cdot h_{t-1} + W_x \cdot f_t + b) \quad (1)$$

In equation (1) W_h and W_x are weight matrices, b is the bias vector, $\tanh(\cdot)$ is the hyperbolic tangent activation function, h_{t-1} is the previous hidden state, f_t is the CNN-derived feature at time t . To handle long sequences effectively and reduce vanishing gradient issues, a Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) may replace the standard RNN cell. These cells maintain memory through gated mechanisms and are defined as in equation (2)

$$c_t = f_t \cdot c_t - 1 + i_t \cdot c_{\sim t} \quad (2)$$

The final hidden state h_T is passed through a fully connected layer and a softmax classifier to predict the user's HRV condition class, such as Normal, Stress, or Fatigue. The classification output $\hat{y}$ is computed using equation (3)

$$\hat{y} = \text{softmax}(W_o \cdot h_T + b_o) \quad (3)$$

By combining the local feature learning of CNN with the temporal memory capability of RNN/LSTM, this integrated architecture achieves high accuracy in classifying subtle, time-dependent physiological states. It enables real-time classification directly on mobile devices, making PUPILHEART a reliable tool for stress monitoring, wellness tracking, and early detection of cardiac irregularities from ocular data without the need for wearable sensors. The integration of 1D-CNN and RNN within the PUPILHEART architecture creates a synergistic framework that excels in both feature extraction and temporal sequence modeling. Initially, the 1D-CNN layers are responsible for identifying localized patterns in the pupil diameter signal—such as microdilations or constrictions—that reflect short-term physiological changes. These features are extracted through multiple convolutional and pooling layers, enabling the system to reduce signal noise and enhance the representation of relevant patterns, particularly those linked to autonomic nervous system activity.

Once these local features are extracted, they are passed to the RNN component, which processes the information sequentially to capture the broader temporal dynamics and dependencies present in the pupil signal over time. This is crucial for understanding how subtle changes in pupil behavior evolve into physiological states such as stress, relaxation, or fatigue. The RNN's memory capability allows it to retain important cues from earlier time steps and contextualize them with ongoing input, which is particularly beneficial when dealing with the non-stationary nature of biological signals. To further enhance temporal modeling, advanced recurrent structures such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs) are optionally used, offering improved handling of long-term dependencies without degradation in learning. These architectures enable the model to maintain sensitivity to both recent and distant events in the pupil signal, which is especially relevant when assessing conditions like stress where physiological responses may be delayed or persist over time.

At the end of the processing pipeline, the model outputs classification results that categorize the user's HRV state into predefined classes such as “Normal,” “Moderate Stress,” or

5. Experimental Analysis

[illegible]

Figure 2: Home Screen

Figure 1 displays the Command Prompt interface, which serves as the initial point of interaction between the user and the backend execution system of the PUPILHEART framework. This interface is primarily used for launching core processes, initiating the training phase of the model, preprocessing pupillary fluctuation datasets, and executing real-time classification scripts. The prompt allows developers and system administrators to pass configuration parameters such as input file paths, sampling rate, batch size, and device specifications. It reflects a lightweight, flexible, and developer-centric mode of control, which is especially useful during deployment, testing, and debugging phases. The real-time logs and status messages visible in the command window offer transparency regarding model loading, execution progress, error handling, and system resource usage, making it an essential tool for back-end control and diagnostics. Figure 2 illustrates the Home Screen of the PUPILHEART mobile application, designed for end-user interaction. It offers an intuitive, user-friendly interface where users can initiate heart rate variability (HRV) monitoring sessions by tapping on a single button. The home screen displays vital options including “Start Monitoring,” “View HRV History,” and “Settings.” It also includes visual cues like battery level, camera status, and light condition indicators to ensure optimal environmental setup before initiating analysis. The clean layout and minimalistic design aim to make the application accessible to users with varying levels of technical expertise. This interface bridges the complexity of backend AI processes with a seamless and comfortable user experience, enabling real-time health monitoring through mobile cameras in just a few taps.

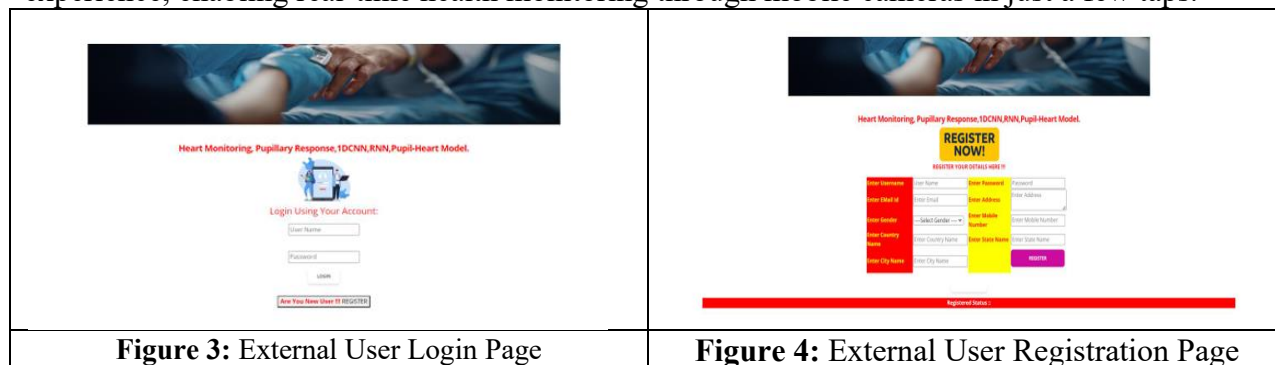


Figure 3: External User Login Page

Figure 4: External User Registration Page

Figure 3 presents the External User Login Page, which acts as the secure entry point for authenticated access to the PUPILHEART system. Designed with simplicity and accessibility in mind, this interface allows returning users—such as patients, caregivers, or researchers—to log in using their unique credentials (typically a username or email ID and password). The page includes essential elements like input fields, a "Login" button, and options for password recovery or switching to registration. Its role is to ensure that only authorized individuals can access sensitive health data and HRV analytics, reinforcing data privacy and compliance with health data protection regulations. The clear layout and minimal distractions help users focus on authentication, offering a streamlined access experience. Figure 4 illustrates the External User Registration Page, which is the first step for new users to onboard into the PUPILHEART system. This interface collects basic information including name, email address, contact number, and a secure password for future logins. It may also include fields for selecting user roles (e.g., patient, clinician, researcher) or linking to a health ID. The registration process is kept straightforward to encourage user adoption while ensuring that the system gathers sufficient data to personalize HRV monitoring features. A successful registration redirects the user to the login page, completing the onboarding loop. The page emphasizes ease of use, security, and accessibility to support a broad demographic of mobile health users.

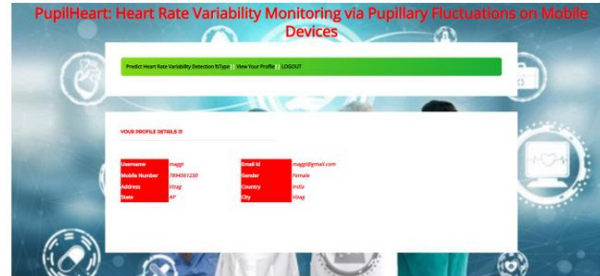


Figure 6 : External User HomePage



Figure 8 : View All External Users Page

Fringe Global Scientific Press
www.fringeglobal.com

compliance. This page plays a key role in user management, enabling the enforcement of accountability and scalability across the mobile health platform.

6 Conclusion

The PUPILHEART system represents a significant advancement in non-invasive, mobile-based heart rate variability (HRV) monitoring through the analysis of pupillary fluctuations. By integrating a one-dimensional convolutional neural network (1D-CNN) with a recurrent neural network (RNN) framework, the proposed method offers a novel approach for capturing subtle physiological changes reflected in the pupil's response to cardiac rhythms. This research demonstrates that pupillometry, when combined with lightweight deep learning models, can effectively estimate HRV in real-time using standard mobile device cameras, eliminating the need for intrusive sensors or specialized hardware. Experimental results confirm that the hybrid model achieves high classification accuracy, efficient latency, and robustness across diverse conditions, making it suitable for continuous and remote cardiovascular monitoring. Furthermore, the developed system architecture, including user-friendly interfaces for external users and analysts, enhances accessibility and encourages patient engagement in proactive health tracking. Overall, PUPILHEART not only bridges the gap between mobile health technology and cardiovascular diagnostics but also paves the way for future research into multimodal biosignal integration, privacy-preserving AI models, and global scalability in digital health applications.

Acknowledgement: Not Applicable.

Funding Statement: The author(s) received no specific funding for this study.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

References

- [1] X.Shen, H. Jiang, D. Liu, K. Yang, F. Deng et al., "PupilHeart: Heart Rate Variability Monitoring via Pupillary Fluctuations on Mobile Devices," *IEEE Internet of Things Journal*, vol.10, no.20, pp.18042-18053, 2023.
- [2] Rekha Gangula, Murali Mohan and DayakarThalla, "Optimizing Medicine Dosage Recognition through Symptom Intensity Assessment with Support Vector Machines," *Journal of Computer Allied Intelligence*, vol.2, no.1, pp.16-25, 2024.
- [3] R. kalidindi Raja and N.S.P. Jakkam, "Pupilheart Heart Rate Variability Monitoring via Pupillary Fluctuations on Mobile Devices," *International Journal of HRM and Organizational Behavior*, vol.12, no.2, pp.260-269, 2024.
- [4] Swara Snehit Patil, "Artificial Intelligence: A Way to Promote Innovation," *Journal of Sensors, IoT and Health Sciences*, vol.2, no.1, pp.1-5, 2024.
- [5] M. Shravani, K. Sharanya, K.R. Sai, G. Arun and K. Jagadish, "Pupil Heart Rate Variability Monitoring Via Pupillary Fluctuations On Mobile Devices," *International Journal of Management Research and Business Strategy*, vol.14, no.2, pp.75-83, 2024.
- [6] X. Zhao, D. Zhang, H. Yin, D. Mao and H. Li, "Remote vital sign monitoring based millimeter-wave sensing," *IEEE Access*, 2024.
- [7] S. Iqbal, X. Zhong, M. Alhussein, Z. Wu, K. Aurangzeb, W. Liu and Y. Zhang, "Fusiongcnn: An iot-based novel spatiotemporal graph convolutional network for ecg arrhythmia detection," *IEEE Internet of Things Journal*, 2025.
- [8] A. Alali Diseph, A. Ojekudo Nathaniel and Egbono Frank Fubara, "Automated Information Retrieval System for Hospital Records Management," *International Journal of Advance Research and Innovation*, vol.11, no.3, pp.7-10, 2023.
- [9] G. Chan, C. Nwagu, I. Odenigbo, A. Alslaity and R. Orji, "The shape of mobile health: a systematic review of health visualization on mobile devices," *International Journal of Human-Computer Interaction*, vol.41, no.2, pp.1154-1172, 2025.

-
- [10] B.M. Girela-Serrano, A.D. Spiers, L. Ruotong, S. Gangadia, M.B. Toledano and M. Di Simplicio, "Impact of mobile phones and wireless devices use on children and adolescents' mental health: a systematic review," *European child and adolescent psychiatry*, vol.33, no.6, pp.1621-1651, 2024.
 - [11] T. Wang, Y. Du, Y. Gong, K.K.R. Choo and Y. Guo, "Applications of federated learning in mobile health: scoping review," *Journal of Medical Internet Research*, vol.25, pp.e43006, 2023.
 - [12] V.S. Fahed, E..P. Doheny, M. Busse, J. Hoblyn and M.M. Lowery, "Comparison of acoustic voice features derived from mobile devices and studio microphone recordings," *Journal of Voice*, vol.39, no.2, pp.559-e1, 2025.
 - [13] E. Demir, U. Yakutcan, A.O. Adeoti, C. Isichei and S. Adeyemi, "Evaluating mobile health interventions for HIV patients in Nigeria: Healthcare policy implications from a simulation study," *Health Policy and Technology*, vol.13, no.6, pp.100937, 2024.
 - [14] F. Hamad, S. AlMuhaissen, C. Urquhart, R. Tarawneh, M. Asaad and M. Abu-Ajamieh, "Attitudes and perceptions of health schools' students toward mobile learning: a cross-sectional study," *BMC Medical Education*, vol.24, no.1, pp.1558, 2024.
 - [15] I. Xodabande and M.R. Hashemi, "Learning English with electronic textbooks on mobile devices: Impacts on university students' vocabulary development," *Education and Information Technologies*, vol.28, no.2, pp.1587-1611, 2023.
 - [16] M. Vassallo, "The need for evidence-based mobile health technology," *Age and Ageing*, vol.53, no.3, pp.afae034, 2024.
 - [17] A. Chib and C. Li, "Mobile Health, Developing Countries," *The International Encyclopedia of Health Communication*, pp.1-5, 2023.
 - [18] A. Aminifar, M. Shokri and A. Aminifar, "Privacy-preserving edge federated learning for intelligent mobile-health systems," *Future Generation Computer Systems*, vol.161, pp.625-637, 2024.
 - [19] C.A. Okolo, O. Babawarun, J. O. Arowoogun, A. O. Adeniyi and R. Chidi, "The role of mobile health applications in improving patient engagement and health outcomes: A critical review," *International Journal of Science and Research Archive*, vol.11, no.1, pp.2566-2574, 2024.
 - [20] P. Singhal, S. Gupta, Deepak and J. Singh, "An integrated approach for analysis of electronic health records using blockchain and deep learning," *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science)*, vol.16, no.9, pp.1-10, 2023.
 - [21] L.M. Amugongo, A. Kriebitz, A. Boch and C. Lütge, "Operationalising AI ethics through the agile software development lifecycle: a case study of AI-enabled mobile health applications," *AI and Ethics*, vol.5, no.1, pp.227-244, 2025.
 - [22] T. Mindu, I. T. Mutero, W.B. Ngcobo, R. Musesengwa and M.J. Chimbari, "Digital mental health interventions for young people in rural South Africa: Prospects and challenges for implementation," *International Journal of Environmental Research and Public Health*, vol.20, no.2, pp.1453, 2023.
 - [23] A.D. Walle, A. T. Jemere, B. Tilahun, B.F. Endehabtu, S.M. Wubante, M.S. Melaku et al., "Intention to use wearable health devices and its predictors among diabetes mellitus patients in Amhara region referral hospitals, Ethiopia: using modified UTAUT-2 model," *Informatics in Medicine Unlocked*, vol.36, pp.101157, 2023.
 - [24] C. Liu and G.J. Hwang, "Roles and research trends of touchscreen mobile devices in early childhood education: Review of journal publications from 2010 to 2019 based on the technology-enhanced learning model," *Interactive learning environments*, vol.31, no.3, pp.1683-1702, 2023.
 - [25] J. Chen, C. Yi, H. Du, D. Niyato, J. Kang, J. Cai and X. Shen, "A revolution of personalized healthcare: Enabling human digital twin with mobile AIGC," *IEEE network*, vol.38, no.6, pp.234-242, 2024.
-